Fraunhofer ISI Discussion Papers *Innovation Systems and Policy Analysis* No. 34
ISSN 1612-1430
Karlsruhe, May 2013

Patents as indicators for knowledge generation and diffusion in mechanical engineering and green biotechnology - A first assessment

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1 Introduction

This study includes two expert reports, which are based on each other. At the core of the first expertise is the analysis of the patent application structures within the technological field of mechanical engineering and their evolution over time at an international level. Secondly, building on the first expertise, a field comparison of mechanical engineering and green biotechnology is performed with the help of a patent analysis.

Mechanical engineering is one of the most important sectors in the German economy and contributes highly to the German gross domestic product, to employment and value added. The innovative success of German engineering is on the one hand based on rigorous research and development services, but on the other hand also on a high level of flexibility and customer focus (Som et al. 2010). Thus, the success of engineering is not only dependent on formal or explicit knowledge, but – more than in science-driven sectors such as chemistry or biotechnology – also on non-explicable or implicit knowledge.

In theory, the mechanical engineering sector, whose technology is largely based on tacit knowledge, should be characterized by a relatively low patent activity. The absolute number of patent applications within this technology field, however, shows a contrary finding. At least for patent applications from German inventors, it can be shown that the number of patent applications at the European Patent Office (EPO) filed in the field of mechanical engineering is higher than in any other technological field. The proportion is relatively stable over the years and lies at just over 40% followed by chemistry, which is the second largest field with about 30% in the recent years. A look at the absolute figures also reveals that the number of filings has almost doubled from 1995 to 2005. While in 1995 nearly 6,000 applications had been filed, it was more than 10,000 in the year 2005. Mechanical engineering can thus be regarded as the most patent active technology field in Germany.

However, it has been shown by Blind et al. (2003) that - in comparison to other technology fields - mechanical engineering (as well as the automotive industry) shows quite a low patent intensity, i.e. the number of patents in relation to the cost of research and development and also in relation to the workforce.

In contrast, the chemical industry or the electrical engineering sector is clearly more patent-intensive. In other words, due to the high R&D expenditures in engineering, one would expect an even higher number of patent applications if the relation of R&D expenditures and patent outcome would be similar to, for example, to chemistry.

Moreover, it has also been shown that the internationalization of German engineering is significantly lower than the internationalization of chemistry. In engineering, only about half of the patents that have been registered at the German Patent and Trademark Office (GPO), have also been registered at the European Patent Office (directly or via the Patent Cooperation Treaty (PCT) procedure). In chemistry, this share is about 90%. As a study of Kinkel et al. (2008) could demonstrate, a lot of the engineering patents stem from small and medium-sized enterprises (SMEs) that operate in research and development less frequent and less continuous on average (Rammer/Spielkamp 2006).

In one of their publications, Schmoch et al. (2003) also calculated the correlation between patent activity (quantitative) and economic performance. A positive correlation was found for engineering as well as for the automotive industry (slightly higher for engeneering), although it is weaker compared to the rest of the "high-tech" fields. This result can be associated with the growing electronification in mechanical and automotive engineering and thus with the increasing importance of explicit knowledge.

To investigate the question of whether mechanical engineering is heavily dependent on tacit knowledge, first of all the patent application structures and their development over time will be analyzed. It can be assumed that particularly larger companies with patenting activity on global mass markets and medium-sized companies specialized in research and development are the most patent-active. In contrast, those firms who develop and commercialize their knowledge assets in niche markets should rather be specialized in other appropriation strategies than patenting. In examining this question with the help of patent statistics, however, the restriction applies that only patenting entities are recorded. To counteract this problem at least partially, a patent-statistical comparison with green biotechnology will be carried out, a technology field that is much more based on explicit knowledge.

To analyze these questions with quantitative means, specific and high-resolution patent-statistical analyses are needed in order to shed light on the nature of the technologies and the importance of the two forms of knowledge. Thus, not only the number of patent applications, but also the legal status of those applications, their interrelations via patent citations as well as their technological and market-related breadth will be analyzed.

The remainder of the study is structured as follows. Chapter 2 summarizes the main literature on patenting and its interrelation to knowledge generation and diffusion. In chapter 3, the data and methodology for the study will be presented. The fourth chapter shows the descriptive und multivariate results. Section 5 concludes.

2 Literature and Theory

At its very core, a patent is a legal intellectual right granted by an authorized government entity (patent office) to exclusively protect an invention from unauthorized use for a certain period of time (Frietsch et al. 2010). It is coupled with a disclosure requirement, meaning that all information covered by the respective patent has to be disclosed after a given time period. In essence, this means that the patent system offers temporary monopoly to inventors in exchange for their early disclosure of new technologies.

This is due to the nature of innovation, or (technological) knowledge in general. In contrast to traditional goods produced and traded on markets, innovation is characterized by its public good character, implying that the generation of knowledge and its commodification into an innovation suffer from market failures, i.e. lacking incentives for firms acting under economic rationality to invest in research and development activities. Thus, state intervention and the establishment of appropriate institutional arrangements are needed in order to enable private appropriation of innovation rents and to provide future incentives for (private) innovation efforts (Schmoch/Grupp 1990; Stiglitz 1995; Stiglitz 1999).

The implications of the patent system thus are twofold. The first one is to encourage investments and efforts in inventive activities. The second one is to force inventors to disclose their newly developed technologies in order to generate spill-over effects, or externalities, which are supposed to benefit the whole of society. Enlarging the stock of public knowledge is assumed to be critical for both technological and economic development, since society benefits from inventions through technological advancement and ultimately economic growth (Edquist/McKelvey 2000; Lundvall/Foray 1996; Malecki 1991; Nelson/Romer 1996). If a patent covers a significantly new technology it can advance the whole technological field, provide new concepts, tools, and ways of production that facilitate innovations in other fields, and gradually update the level of technological capabilities in the whole society (Frietsch et al. 2010).

The growth of the world economy and the progressing globalization lead to a rapidly expanding access to information and new markets for inventors, resulting in greater international competition and new forms of organization. As a result of technological advances and the increased flow of information, knowledge is increasingly viewed as the driving force of economic growth and innovation (OECD/Eurostat 2005).

An invention, however, does not necessarily translate itself into an innovation. An invention is "[...] a research and development driven initial technical realization of a new problem-solving mechanism" (Pleschak/Sabisch 1996). This means that an invention exclusively represents technical information which might have an economic value in the future. Thus, an invention can in many cases be viewed as an initiator for an innovation. To qualify as an innovation, however, an invention alone is not sufficient, as the innovation process encompasses all stages from planning to research and invention to commercialization and implementation. Only the result of a full innovation process, i.e. a new product or a new process, can be viewed as innovation (Grupp 1997).

Still, the successful completion of the innovation process alone is not a sufficient condition to obtain the expected benefits from innovation, since firms also have to be able to appropriate these benefits, i.e. to prevent its competitors from imitating their results (Hanel 2008). This can be achieved via patenting or other Intellectual Property Rights (IPRs) but also by rather informal appropriation mechanisms like keeping an invention secret or utilizing lead-time advantages (Blind et al. 2006; Neuhäusler 2012).

2.1 The interrelation between patents and knowledge generation

In light of the unfolding global competition, knowledge can be considered as an intangible asset, which is a critical resource in the technology competition (Willke 1998). Thereby, it is central to transfer individual into organizational knowledge so that the company as a whole can benefit from it (Song/Chermack 2008). Besides the generation of (implicit as well as explicit) knowledge, inter-individual knowledge transfer is a core component in enhancing the (innovative) performance of a company. Particularly tacit or implicit knowledge is said to be of great importance for these knowledge exchange processes (see for example Polanyi 1985; Prange 1996). However, it is also highlighted that organizational innovative knowledge can only be created through a continuous dialogue between tacit and explicit knowledge (Nonaka 1994; Rammert 2003). The transitions between explicit and tacit knowledge have to be transferred into routinized organizational processes in order to build up expert know-how. Within the course of this process, individual knowledge is articulated and made available to the public, resulting in performance improvements (Willke 1998).

For a more in-depth understanding, it is necessary to differentiate the various forms of knowledge. Knowledge is closely linked to people who have a specific experience or background. Staff's knowledge thus serves as a basis for knowledge in organizations (see for example Prange 1996; Willke 1998). An increase in individual knowledge within an organization thus results in an increase in the knowledge of the whole organization.

However, we also know a form of knowledge that exists separately from the knowledge of specific individuals and thus represents an added value to the mere sum of the knowledge of the individual members. Organizational knowledge generation can therefore be seen as the ability of companies to create new knowledge, distribute it within the organization and to integrate it into new products, systems and services (Nonaka/Takeuchi 1995). However, it is largely unknown how this type of organizational knowledge is generated and distributed. Willke (1996) emphasizes the codified or explicit form of relevant organizational knowledge, while Prange (1996) emphasizes the aspect of implicit or tacit knowledge.

The concept of implicit knowledge (tacit knowledge) was introduced by Polanyi (1985) and specifies personal experiential knowledge or know-how, which has a specific character and is bound to the particular context of its generation (Foray 1997). This knowledge is inherently difficult to communicate, but can be transferred by personal communication or demonstration (Schmoch 2003). In contrast, explicit or codified knowledge is coded using characters (written language). Thus, it can be easily communicated, transferred and stored.

2.2 Benefits of patents as sources of explicit knowledge

Patents can be seen as a representation of codified knowledge (Grupp 1998). Thus, one basic assumption of patent indicators is that they reflect the knowledge capabilities or the knowledge stocks of the patenting entities (mostly companies but also universities or public research institutes as well as single inventors) and – in a wider perspective – also of whole nations (Frietsch/Schmoch 2006). A patent may have no direct value for the firm or an innovation system, but it is at least a part of a technological trajectory from which the firm expects to generate an economic or strategic value.

However, patents – as codified knowledge sources – do not only carry value for the patent owner himself but also to others as the patent document discloses the complete information behind the patented invention to the public. A published patent document thus also has certain social benefits as others can build their own R&D upon this codified knowledge. An investigation by Trajtenberg (1990) for example measures the benefits for users of a medical device and proves patent-weighted citation counts to be an adequate means to predict these benefits. Thus, patents (and R&D leading to developing the patented inventions) have what is called spill-over benefits. Geographic spill-overs of R&D are well known phenomena (Griliches 1992; Jaffe 1986). Likewise, many studies provide empirical evidences of spill-overs from patented technologies to the technological capacities of companies (Jaffe et al. 1993; Jaffe et al. 1998; Jaffe et al. 2000).

Those spill-overs are commonly measured by patent citations, which are able to indicate knowledge flows because they codify the passage of ideas (Jaffe et al. 1993).

2.3 The patent indicators – What do they measure?

Before digging deeper into the data, in this section we introduce the patent indicators that will be used in the following analyses. Patents are among the most important indicators for the output of R&D processes and are frequently used to assess the technological performance of firms, technology fields and economies as a whole (Freeman 1982; Grupp 1998). A large amount of patents thus indicates strong efforts in R&D activities and therefore a higher innovative output. However, large patent portfolios are also strategically useful, for example, to block competitors in the same or adjacent technological areas or prevent especially smaller potential competitors from entering relevant markets (Blind et al. 2006; Blind et al. 2009; Neuhäusler 2012).

Besides the indicator function of patent filings as such, patents bear a large amount of additional information, e.g. references to previous patents and scientific publications or the outcome of the examination process. This information can be used by researchers to indicate for example the development of new technological trajectories, the pace of technology cycles, the science-link of a patent or the economic and technological quality of patents.

In order to draw a more complete picture of patenting activities in the mechanical engineering and the green biotechnology sector and to compare the two technology fields, several of these patent-related indicators will be employed. Yet, before, their meaning and implications will be reviewed below.

The number of citations a patent receives from subsequent patent applications, commonly called *forward citations*, probably are the most common and widely used patent-related indicator. Many scholars argue that forward citations, besides indicating technological spill-overs, are able to indicate the technological as well as economic value of a patent (Narin et al. 1987; Trajtenberg 1990). The basic assumption is that the number of forward citations measures the degree to which a patent contributes to further developing advanced technology, thus this can be seen as an indicator of technological significance (Albert et al. 1991; Blind et al. 2009; Carpenter et al. 1981). Turning the argument the other way round, also *backward citations* (citations given in a patent) refer to previous patents and are mostly used as an indicator of technological breadth or background of an application and can give hints on the scope of a patent (Harhoff et al. 2003). Yet, it can also be interpreted as a measure of „originality“: Patents with a large number of backward citations can be assumed to build on a broad basis of already existing knowledge, whereas patents with only few backward citations only have a small existing knowledge stock to build upon (Fernández-Ribas 2010; Rosenkopf/Nerkar 2001). Besides previous patents, also scientific publications can be cited in a patent application. These references to non-patent literature (*NPL-citations*) can be used to indicate the closeness to sciene or basic research of a patent applicant's R&D activities (Deng et al. 1999).

Besides to citation-based indicators, the legal status of a patent application is able to give hints on the technological value of a patent. Specifically, we can look at the outcome of the patent examination process, i.e. if a patent has been granted, withdrawn or refused. The interpretation is quite straightforward for *granted patents*. A granted patent implicitly represents the technological value of a patent. A granted patent implicitily represents an invention of technological value - and is hence more valuable than a non-granted patent as it has met the criteria of novelty, technological height, and industrial applicability (Frietsch et al. 2010). The opposite is true for *refused patents*. A refusal clearly indicates that the given patent application did not meet the standards for being granted (novelty, technological height and industrial applicability). For *withdrawals*, however, things become a little more complicated. A patent withdrawal can indicate different things. It may only be an anticipation of a future refusal (compare for example Harhoff/Wagner 2009). On the other hand, withdrawn patents can also have had a strategic (e.g. blocking) value during their existence (Blind et al. 2006). Furthermore, a withdrawal decision can reflect the successful product portfolio management of a firm and be a result of strategic decisions like giving up business in a certain technological field.

Another legal status indicator is patent oppositions, which can be filed by any third party up to nine months after a patent has been granted by the patent office.[1] Oppositions can be interpreted as an indicator of the technological value of a patent since opposing a patent is subject to significant additional costs, for which the opposing party should only be willing to pay if there is a market for one of their inventions which is to be covered by the contested patent. In addition, an appeal against a patent means that at least two parties conduct research for exactly the same piece of technology. Therefore, the cost and risks associated with the dispute signal the existence of a market for the patented invention (Van Zeebroeck 2009). In practice, however, opposition is a rare event, as for example only about eight to nine percent of all EPO patents are challenged (Harhoff/Reitzig 2004). Finally, we will also take a look at how long a patent is

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[1] An opposition against a patent directly at the patent office is a rather rare event especially in the US, where patents are mostly litigated in court.

renewed at the patent office. We proxy this by an indicator that measures if any kind of fee has been paid to the patent office at least five years after priority filing. This is supposed to indicate if a patent is marketable and the applicant is willing to pay a certain fee to maintain the patent, implying that it is worth at least as much as the renewal fee that has to be paid to the patent office (Bessen 2008; Schankerman/Pakes 1986; Schubert 2011).

Besides legal status indicators, there are two additional indicators that measure the breadth of a patent application in a certain sense. The number of IPC (International Patent Classification) classes, which are assigned by the patent examiner, indicate the technological breadth of a patent application (Lerner 1994). In order to capture the breadth of a patent application in terms of the markets it covers, the family size of patent application can be employed. It is determined by the number of countries or patent offices at which a patent has been applied (Putnam 1996; Schmoch et al. 1988). Therefore, it provides information about the number of markets that are sought to be secured by the applicant to sell his invention. Since the costs for applying and upholding patents in foreign countries are high, it can be assumed that an applicant is only willing to bear those costs if he expects a corresponding profit. Thus, the size of the patent family can implicitly be interpreted as an indicator of (economic) patent value. Both, technological as well as market breadth can be assumed to serve as a hedge against possible risk, e.g. if a market fails there is another potential market on which a product incorporating a specific technology can be sold exclusively.

The two final indicators that shall be discussed here are the technology cycle time as well as the international orientation of a patent filing. The technology cycle time is a citation-based indicator and is supposed to indicate the speed of innovation. It is calculated as the median age of the cited patent documents. Aggregated at the technology field level, shorter technology cycles indicate that a technology field is moving faster from old to new technologies (Deng et al. 1999; Narin 1993). In order to indicate the international orientation of a patent filing, one can find out if an application is filed at the respective national office (i.e. the German Patent Office (GPO) or the United States Patent and Trademark Office (USPTO)) as well as the EPO. In contrast to the family size, which rather covers the breadth of a patent application in terms of the markets it covers, the international orientation indicates the internationalization of a technology, i.e. how far technologies target purely a national or rather an international market.[2]

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[2] Since our dataset is at the level of single patent applications, this indicator cannot be used in the multivariate models but is only available for descriptive statistics.

On an aggregated technology field level, it is calculated as the share of EPO patent filings from German or US applicants in relation to national patent applications at the respective patent office.

2.4 Data

The data we use for the study were extracted from the "EPO Worldwide Patent Statistical Database" (PATSTAT), which provides information about published patents collected from 81 patent authorities worldwide. We focus our analyses on patent applicants from Germany and the USA. Counting patents by the country of the applicant means that each patent is assigned to the country from which the patent has been filed, implicitly accounting for the fact that larger firms might apply all their patents for example from the country where their headquarters or main research facility is located. Therefore, a patent filed by a US applicant is counted as a patent originated from the USA.

All patent data applied here follow the "German market" concept, i.e. patents targeting the German market. In detail, all patents directly filed at the German Patent Office (GPO) as well as all applications at the EPO are counted (including the patent applications forwarded to the EPO from the World Intellectual Property Organization (WIPO) via the Patent Cooperation Treaty (PCT) procedure). In the case of German applicants, it can be assumed that patent applications filed at the EPO will sooner or later be forwarded to the GPO to cover the German market. We thus only count patents directly filed at the GPO as well as all EPO patents by German applicants. Patents at the GPO that were forwarded from the EPO are excluded to avoid double counting.

We apply the same concept for US applicants, although our concept does not necessarily hold for US applicants or at least the rate of patents filed at the EPO and then transferred to the GPO should be smaller for US applicants than for German applicants. Yet, this method allows us to include all patents for which protection is sought in Germany, or for the German market, without double counts for German as well as US applicants.

All the patents in the dataset are counted according to their year of worldwide first filing, the so-called priority year. This is the earliest registered date in the patent process and is therefore closest to the date of invention. We included all patent filings from the priority years 1985 to 2009.

Technologies in our dataset are differentiated by 34 WIPO classes (Schmoch 2008) as well as 35 high-technology fields, including a residual “low-tech” category (Legler/Frietsch 2007). In order to classify green biotechnology, a special definition based on IPC 4-digit classes was employed.[3] The IPC classification was introduced to systematically order all patents worldwide. Patents are not directly connected with products, but distinguished primarily by their technical implications. The IPC is updated annually and revised every three years, to capture technological change more effectively. Existing data is adjusted to the current version of the IPC, so to speak, it is "classified backwards" (Frietsch 2007; WIPO 2006). In the case of mechanical engineering, the fields power machines and engines, agricultural machinery, machine tools and special purpose machinery from the above mentioned list of high-technology fields were aggregated and together form the broader category of mechanical engineering.[4]

Furthermore, we included a differentiation by the type of the applicant, i.e. if it is a small or medium-sized enterprise (SME), a large multinational enterprise (MNE), an individual inventor or a university or public research institute (Frietsch et al. 2011). Corporate applicants with more than 500 employees and more than three patent filings in a three-year time window between the priority years 1996 and 2008 were classified as MNEs. The number of 500 employees corresponds to the German SME definition (Günterberg/Kayser 2004). The remaining applicants with more than three patent filings in the given time window and less than 500 employees were classified as SMEs.

Finally, we added additional citation-related indicators from the PATSTAT database, like for example patent forward citations, legal status related indicators like patent grants, technology cycle times, as well as the patent family size and the number of IPC classes.

2.5 Variables

We now briefly turn to the variables to be used in our multivariate analyses (Table 1). Following the theoretical discussion from Section 2, we use different kinds of variables as response variables in our models, with two dummy variables for the analyzed technology fields as explanatory dummy variables, i.e. a variable for green biotechnology coded "1" in case the patent is classified as green biotechnology and "0" otherwise as well as a variable for mechanical engineering coded in the same fashion. Table 1 also

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[3] In detail, the IPC 4-digit codes C07G, C07K, C12M, C12N, C12P, C12Q, C12R, C12S and A01H were used to define the field of biotechnology.

[4] At this point, it is important to mention that the mechanical engineering sector is defined relatively narrowly, i.e. excluding transportation like automobiles and cars. This means that the results from section 3.1.1 cannot be compared directly to the results mentioned in the introduction, where a very broad definition of mechanical engineering was used.

shows if a variable is used as a response, explanatory or control variable in the following models.

Regarding the legal status of patent filings, which indicates if a patent has been granted, withdrawn, refused during the examination process, or opposed after grant, the Patent Register Service (PRS) codes were employed, which are assigned to each patent application by the respective patent office. Based on this information, dummy variables were created, which indicate if a patent has been granted (coded 1 for yes, coded 0 for no), withdrawn, refused or opposed during examination process (or after, in case of oppositions). The same methodology was used to generate the variable on fee payment. It is coded 1 if the maintenance fee for the patent has been paid for at least five years and 0 if there was no fee payment PRS code assigned. The data for the maintenance fees, however, are only available for EPO filings. Thus, analyses including information on the maintenance fees are limited to the EPO only.

Besides the legal status variables, citation-related variables are used as a response variable in our models. Besides the technology cycle time, these are all count variables. In the case of forward citations, a four-year time window was used. This time window assures that all patents have the same amount of time to be cited. Not using a time window would lead to higher citation counts for older patents, as they had a longer time period to be cited, which would cause a systematic bias. Using a time-window, however, is not necessary for the analysis of backward- and NPL citations, since those references are made to previous documents and thus are not biased by timing effects. The technology cycle time is calculated as the median age of the cited patent documents mentioned in a given patent application and thus gives information on the age of the technology the application refers to.

Table 1: Overview of the variables and summary statistics

Variable	**Usage**	**Obs.**	**Obs. (coded 1)$^{\beta}$**	**Mean**	**Std. Dev.**	**Min**	**Max**
Technology field indicators							
Mechanical engineering	iV	1,503,103	238,394	0.16	0.37	0.00	1.00
Green biotechnology	iV	1,503,103	71,189	0.05	0.21	0.00	1.00
Citation related indicators							
Nr. of forward citations	dV	1,447,563	--	1.77	4.63	0.00	642.00
Nr. of backward citations	dV	1,447,563	--	5.93	9.13	0.00	1,390.00
Nr. of NPL citations	dV	1,447,563	--	2.03	10.52	0.00	2,149.00
Technology cycle time (log)	dV	1,222,176	--	1.84	0.83	-0.69	4.61
Legal status indicators							
Granted	dV	1,368,289	519,987	0.38	0.49	0.00	1.00
Withdrawn	dV	1,368,289	428,368	0.31	0.46	0.00	1.00
Refused	dV	1,368,289	69,051	0.02	0.15	0.00	1.00
Opposed	dV	1,368,289	33,285	0.05	0.22	0.00	1.00
Fee payment (after 5 years)$^{\alpha}$	dV	813,917	282,904	0.35	0.48	0.00	1.00
Additional patent indicators							
Nr. of IPC classes	dV	1,502,609	--	1.88	1.17	1.00	19.00
Family size	dV	1,503,103	--	4.53	3.56	1.00	47.00
Control variables							
US applicant	cV	1,493,412	589,667	0.39	0.49	0.00	1.00
German applicant	cV	1,493,412	903,745	0.61	0.49	0.00	1.00
EPO filing	cV	1,503,103	894,683	0.60	0.49	0.00	1.00
GPO filing	cV	1,503,103	608,420	0.40	0.49	0.00	1.00
SME	cV	1,497,306	345,048	0.23	0.42	0.00	1.00
LME	cV	1,497,306	1,088,053	0.73	0.45	0.00	1.00
University	cV	1,497,306	34,211	0.02	0.15	0.00	1.00
Public research institute	cV	1,497,306	29,994	0.02	0.14	0.00	1.00
Cohort 1 (1985-1989)	cV	1,503,103	138,748	0.09	0.29	0.00	1.00
Cohort 2 (1990-1994)	cV	1,503,103	200,540	0.13	0.34	0.00	1.00
Cohort 3 (1995-1999)	cV	1,503,103	337,386	0.22	0.42	0.00	1.00
Cohort 4 (2000-2004)	cV	1,503,103	429,286	0.29	0.45	0.00	1.00
Cohort 5 (2005-2009)	cV	1,503,103	397,143	0.26	0.44	0.00	1.00

Source: EPO – PATSTAT, own calculations.

Note: $^{\alpha}$ Data available for EPO filings only, $^{\beta}$ only for Dummy variables, dV: Dependent variable, iV: Independent variable, cV: Control variable. The shares of the legal status indicators do not sum up to 100% due to pending patent applications for which there has not yet been a decision by the patent office.

The last two variables under analysis are the family size of a given patent application as well the number of distinct IPC classes (4-digit) that are given on the application. The family size is defined as the number of distinct patent offices where the patent was filed (Martinez 2009; Martínez 2010). Therefore, the family size variable is also a count variable, however, excluding zero counts, which means that it is a censored count variable that requires certain estimation methods (see the description in section 2.6). The same applies for the number of IPC classes.

In order to control for size effects, the differentiation by the type of the applicant, i.e. if it is a small or medium-sized enterprise (SME) or a large multinational enterprise (MNE), is employed. In addition, we also control for the fact whether the patent applicant is a university or a public research institute. Thus, for each of these applicant types a dummy was created that enters our models. We further control for the fact whether a patent has been applied by a US or a German applicant and whether an application is an EPO or GPO application. In the case of both variables, a small specialty occurs. For the correlations and multivariate analyses, in both cases only the information for the first applicant named on the patent application was used. This is a necessary precondition in order to generate distinct categories for the dummy variables, so they can be interpreted correctly.[5] Finally, we include dummy variables for priority year cohorts to control for period-specific effects.

In sum, this leaves us with a final sample of about 1.5 million patents from 1985 to 2009, differentiated by filing office, the type of the applicant, the applicant's country and most importantly the technological field in which a patent application is classified.

2.6 Model specifications

Different types of models with the dichotomous green biotechnology and mechanical engineering explanatory variables as well as dummy variables to control for size effects, country- and time-specific effects were fitted in order to test our hypotheses. We calculated all models separately for EPO applications and patents filed directly at the GPO in order to separate the effects on patent filings that target an international market (EPO) and those filings that purely target the German national market (GPO direct).

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[5] However, for the descriptive and structural analyses, information of all applicants named on a patent application is used, e.g. a patent .a patent which names a US and a German applicant is counted once as a US patent and once as German patent. This can also lead to a situation where the sum of German and US patents exceed the total amount of patents filed.

To analyze the effects on the legal status variables in more detail, logistic regressions were employed, since the outcome variables are dichotomous, i.e. a patent was granted or not, withdrawn or not etc. In the logit model, the log odds of the outcome are modeled as a linear combination of the predictor variables (Long 1997). In the case of the technology cycle time, an OLS regression was used. Since the technology cycle time is not normally distributed, we take the log of this variable for our analyses. For the analyses of citations (forward, backward and NPL), negative binomial regression models were employed, because these variables are in the form of count data. Several kinds of count models exist to address this problem, with the Poisson and the negative binomial regression model probably being the most prominent. The Poisson distribution, however, assumes that mean and variance of the response variable are the same (Long 1997). If the variance is much larger than the mean, the model underestimates the variance and standard errors of the Poisson regression, leading to overly high z-values. A large difference of the mean and variance of those variables can already be observed in Table 1. This overdispersion can be accounted for by a negative binomial regression model, which adds an overdispersion parameter alpha reflecting the unobserved heterogeneity between observations (Long/Freese 2003). A likelihood ratio test on this parameter showed that for all of the variables the negative binomial distribution in this sample is not equivalent to a Poisson distribution and therefore the negative binomial regression model is most suitable for this analysis.

A specialty occurs for the family size and the number of IPC classes variables, since both are zero-truncated variables, i.e. zero counts are not possible. Therefore, we ran a zero-truncated negative binomial regression model for these two variables, because ordinary negative binomial regression would try to predict zero counts even though there are no zero values, leading to biased estimates. Again, likelihood ratio tests showed that the zero-truncated negative binomial model is preferred to a zero-truncated Poisson model in this sample.

3 Results

Within this section, the empirical results of the patent analyses in the mechanical engineering and green biotechnology sectors will be presented. First of all, we will show some descriptive statistics to get an overview of the patenting trends within the two fields (section 3.1). These analyses will be followed by multivariate analyses with the help of the compiled dataset (section 3.2).

3.1 Descriptive statistics

Within this chapter, we start with a descriptive overview by showing patenting structures and trends within the field of mechanical engineering and green biotechnology. In order to give a more complete picture and to be able to assess these results in a broader context, also the total patenting trends will be presented (section 3.1.1). In section 3.1.2, we will present the results of a correlation analysis of the different patent indicators within the two fields.

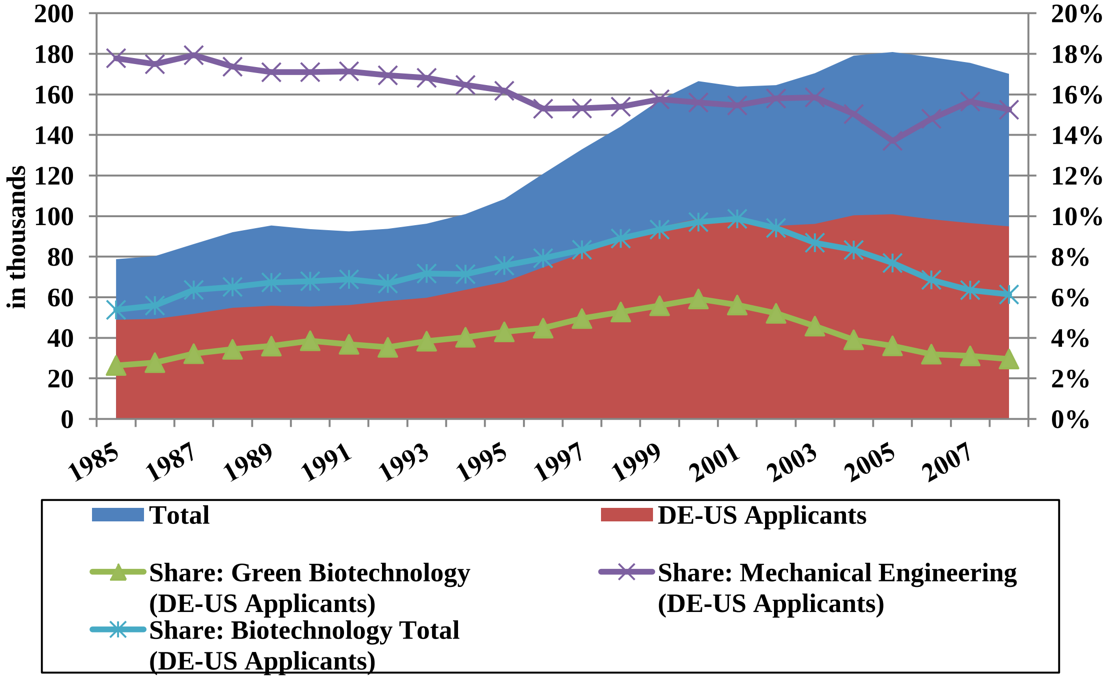
3.1.1 Structures and trends in patenting – The mechanical engineering and green biotechnology sectors

In Figure 1, the total number of patent applications at the EPO and GPO as well as the shares of mechanical engineering and green biotechnology patents for German and US applicants are depicted. First of all, it can be stated that German and US applicants are responsible for about 95,000 patent applications at the EPO and GPO in 2008, which means that these two applicant countries make up nearly 56% of all patent applications covering the German market.

Taking a closer look at the two technology fields of interest, it can be revealed that 14% to 18% of all German and US patents covering the German market stem from mechanical engineering. This high share is not surprising, since Germany is known to be relatively strongly specialized in high-level technologies, especially in engineering. In sum, however, we can see that the trend is slightly decreasing over the years, from 18% in 1985 to 15% in 2008. This can mostly be explained by a decreasing share of patent applications in the mechanical engineering sector from US applicants, especially in the recent years (compare Figure 4 below).

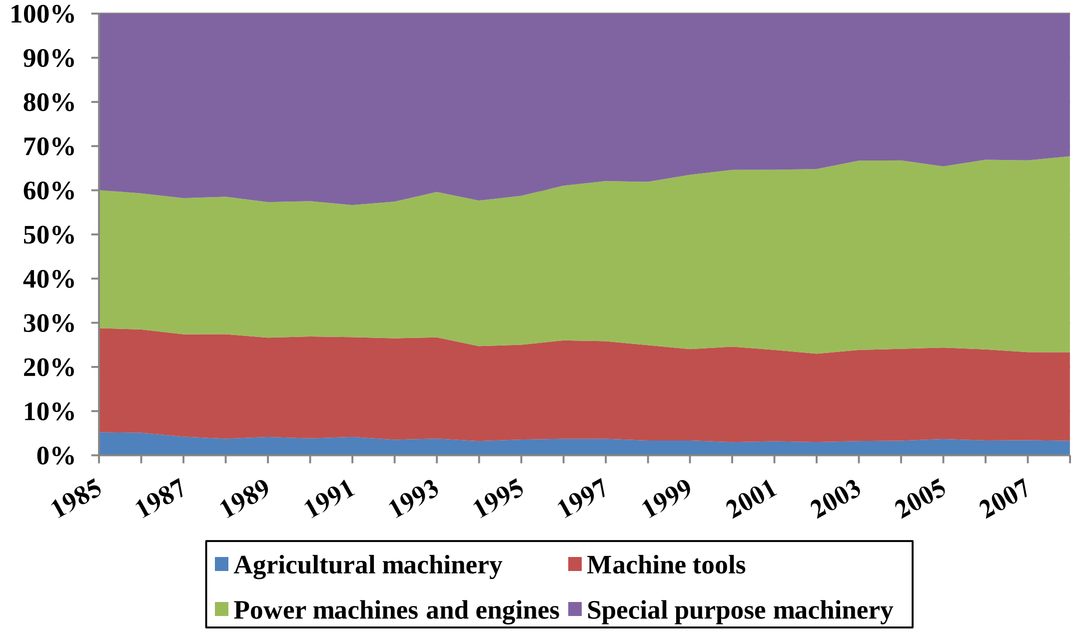
A first look at the shares in green biotechnology reveals that this field is considerably smaller in terms of patent applications covering the German market than mechanical engineering. German and US patents in green biotechnology only reach a share of 3% to 6% on all EPO and GPO patents over the years. It is interesting to see that this share is relatively stable at about 3% in the late 1980s. From 1992 onwards, however, the green biotechnology is growing relatively quickly until 2001. Yet, from then on, the share starts to decrease and is back to its original level of 3% in the year 2008. It is interesting to note that this trend is not a specialty of green biotechnology but can also be found in biotechnology as a whole.

Figure 1: Number of patent applications at the EPO and GPO and shares of mechanical engineering and biotechnology patents for German and US applicants, 1985-2008



Source: EPO – PATSTAT, own calculations.

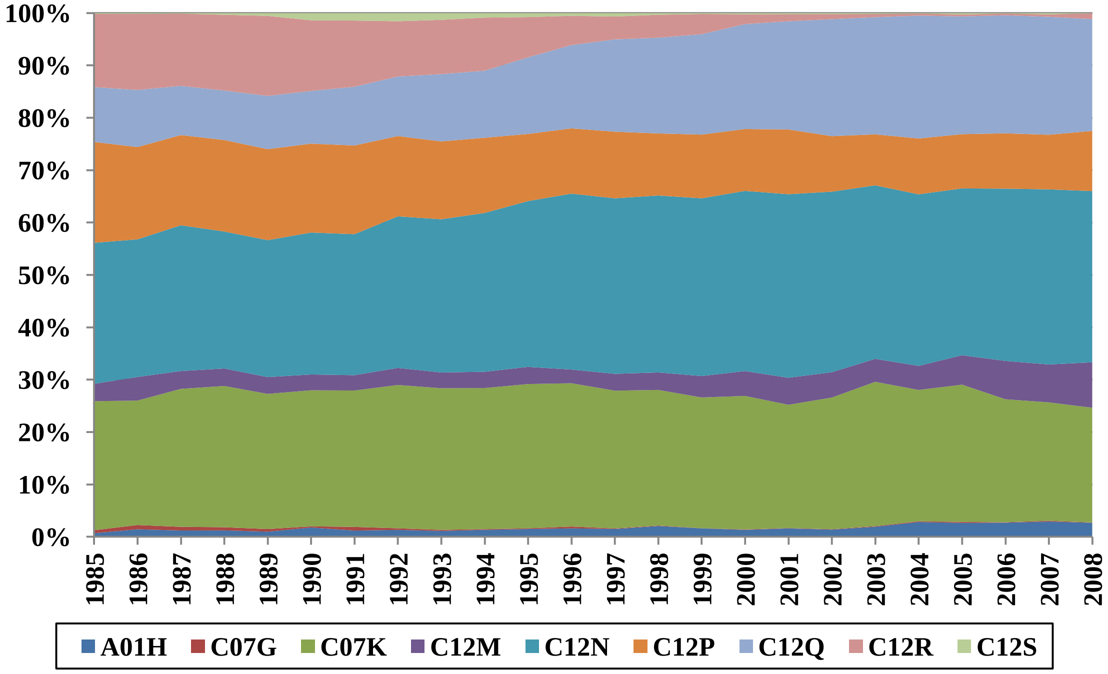
Figure 2: Shares of patents in specific mechanical engineering fields in all EPO and GPO patent applications in mechanical engineering, 1985-2008



Source: EPO – PATSTAT, own calculations.

Taking a closer look a the specific fields within the mechanical engineering sector, it can be revealed that the largest share of GPO and EPO patent applications in 2008 was filed within the field of power machines and engines (about 39%). It is followed by the special purpose machinery field, which was larger than power machines and engines in terms of patents until the mid 1990s, but in 2008 only reaches a share of about 34%. Third largest is the field of machine tools (22%), which is followed by the smallest field in comparison, namely agricultural machinery, reaching a share of only about 5% in the year 2008. The share in the field of agricultural machinery, however, remains mostly stable over the whole time period whereas special purpose machinery as well as machine tools have constantly lost ground over the years. The field power machines and engines is mostly growing over the years, at a quicker pace especially within the 1990s, and is now the largest among the four mechanical engineering fields in comparison.

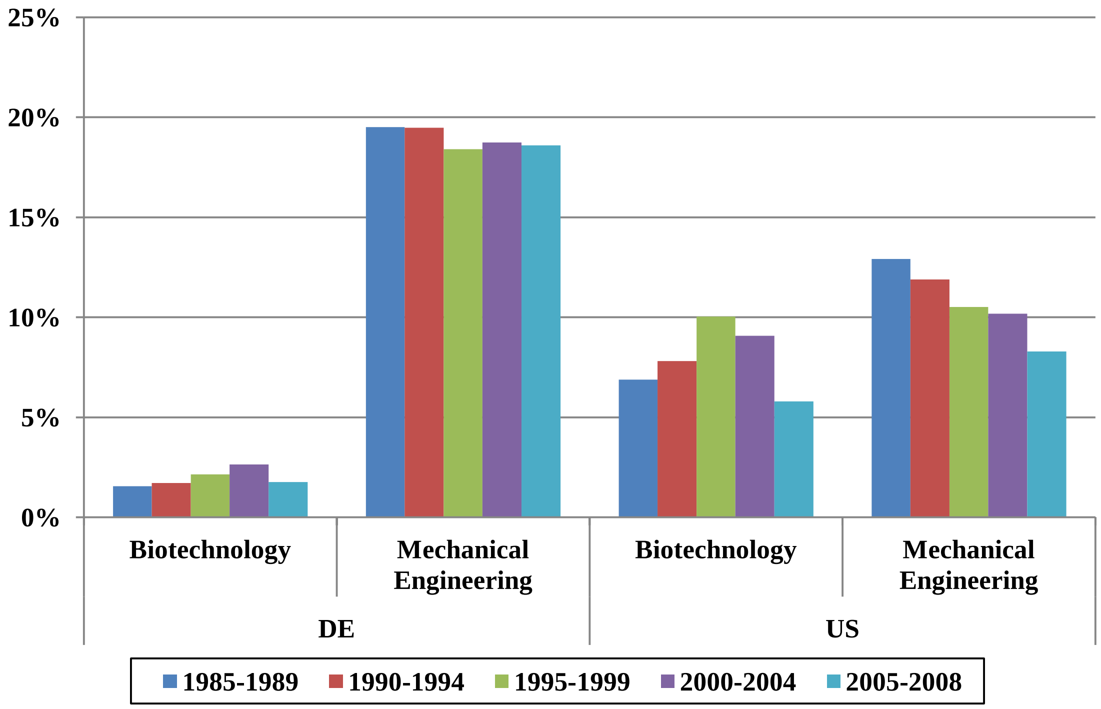
Figure 3: Shares of patents in specific fields in green biotechnology (IPC 4-digit) in all EPO and GPO patent applications in mechanical engineering, 1985-2008



Source: EPO – PATSTAT, own calculations.

A similar analysis can now be conducted for the fields within the green biotechnology at the IPC 4-digit level (Figure 3). It can be found that the largest share of GPO and EPO patent applications in 2008 are filed within the IPC classes C12N "MICRO-ORGANISMS OR ENZYMES […]", C07K "PEPTIDES" and C12Q "MEASURING OR TESTING PROCESSES INVOLVING ENZYMES OR MICRO-ORGANISMS […]". While C12N and C07K are slightly declining in terms of patenting over the years, C12Q is growing relatively strongly, at least from 1993 onwards. This growth, however, can mostly be attributed to a massive decline in IPC class C12R "INDEXING SCHEME ASSOCIATED WITH SUBCLASSES C12C-C12Q, RELATING TO MICRO-ORGANISMS", in which patenting nearly stops from 2000 onwards. Yet, C12R relates to "micro-organisms used in the processes classified in subclasses C12C-C12Q". Similarly, the class C12P "FERMENTATION OR ENZYME-USING PROCESSES TO SYNTHESISE A DESIRED CHEMICAL COMPOUND […]" is declining over the years, however by far not as heavily as C12R.

Figure 4: Shares of green biotechnology and mechanical engineering applications at the EPO and GPO by German and US applicants in all applications of the respective country, 1985-2008



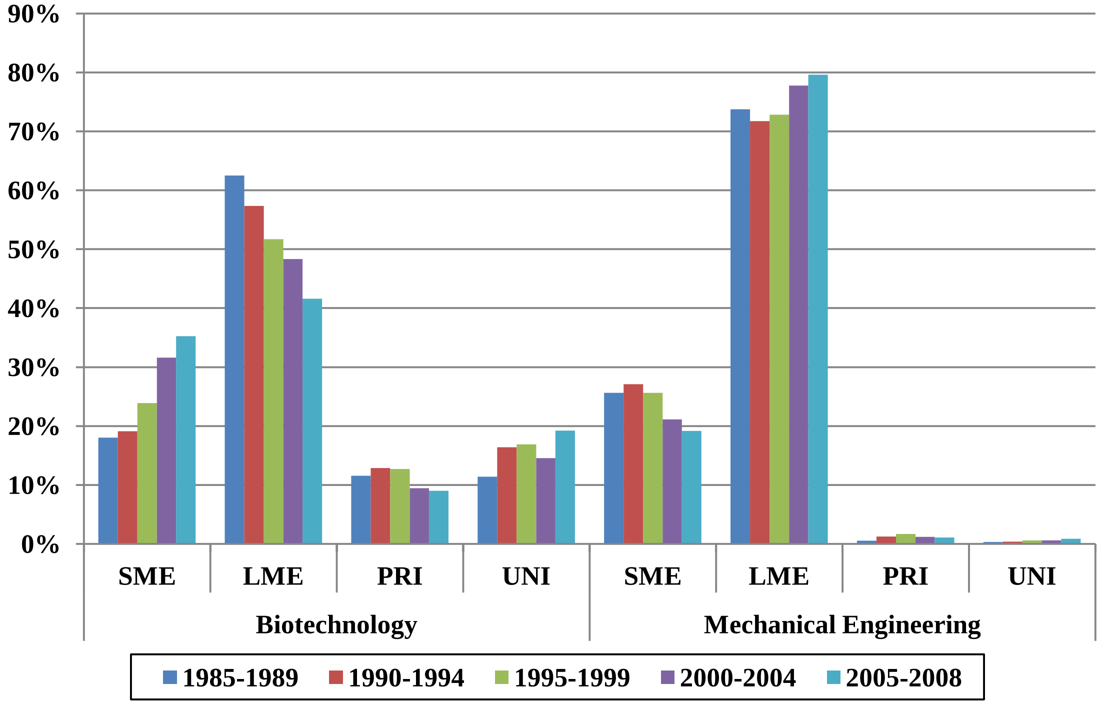
Source: EPO – PATSTAT, own calculations.

In Figure 4, the shares of green biotechnology and mechanical engineering applications at the EPO and GPO for German and US applicants as a share on all patent applications of the respective applicant country are depicted. As can be seen from the figure, the mechanical engineering sector is of relatively great importance in Germany. Nearly 20% of all German patent applications are originating from this technology field, although this share is slightly decreasing over the years. Green biotechnology, on the other hand, is rather small by comparison. Only about 2% of applications filed by German inventors are coming from that field.

For US applicants, the picture is different. Over the years, an average of only 10% of filings within the US portfolio stem from mechanical engineering. In addition, the share for US applicants decreases rather fast over the analyzed five-year periods. In 1985-1989, 13% of the US patent portfolio consisted of mechanical engineering patents, whereas in 2005-2008, this share dropped to only 8%. In green biotechnology, however, the US portfolio is large compared to the German one. Over the years, the share of green biotechnology in all patents ranges from 6% in 2005-2008 to 10% in 1995-1999. It is interesting to note that the trend in green biotechnology – an increase until the late

1990s and a decrease in filings afterwards – is obvious for German as well as US applicants, although it is much stronger for US applicants.

Figure 5: Patent applications by applicant type as a share of total EPO and GPO applications in the respective field, 1995-2008, patent applications from US and German applicants only, single inventors excluded



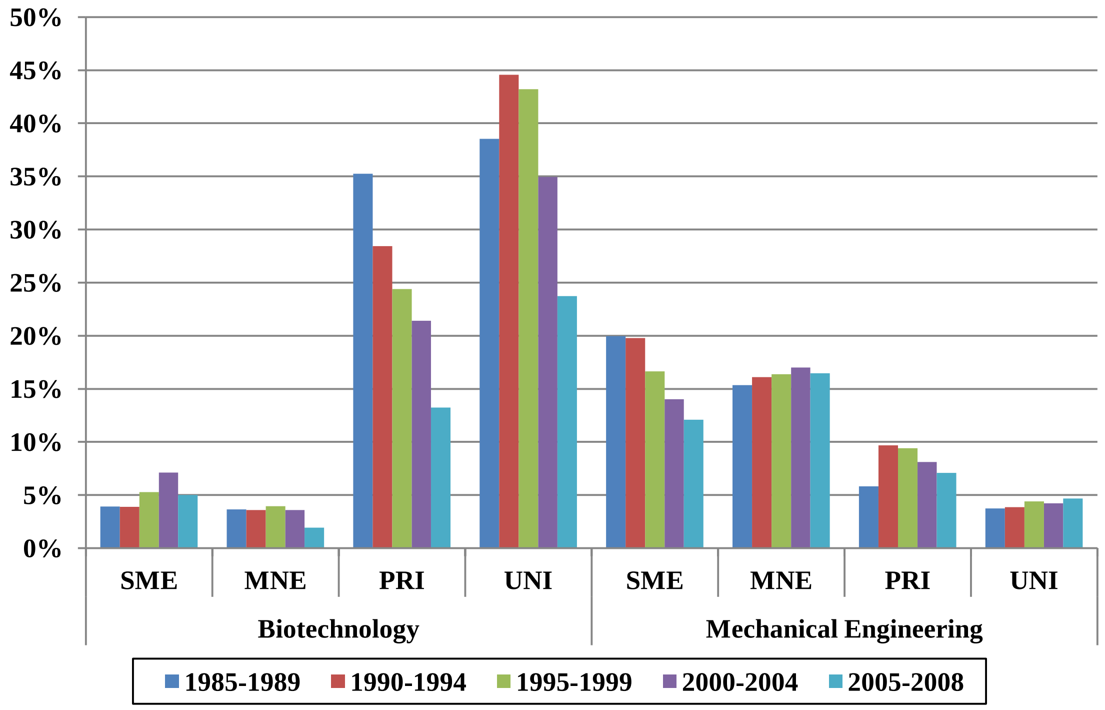
Source: EPO – PATSTAT, own calculations.

Note: The shares might exceed 100% due to co-patents between types of applicants.

Figure 5 shows the number of patent applications in mechanical engineering and green biotechnology separated by the type of the applicant as a share of the total patent applications from industry, universities and public research institutes in the respective field by US and German applicants covering the German market. It becomes obvious that the largest share (nearly 80% in 2005-2008) of patent applications within mechanical engineering is filed by large multinationals. This trend is increasing slightly over the years. In the case of SMEs, the trend is curve linear. It increases from 26% in 1985-1989 to 27% in 1990-1994 and afterwards starts decreasing down to 19% in 2005-2008. Universities and public research institutes both only make up about 1% of patent applications within the field. All in all, this resembles a relatively typical picture of a quite mature technology field: basic research, where universities and public research institutes are typically located, is more or less completed, large firms are established and the technology is diffused to the market.

This picture, however, is totally different for green biotechnology, which is a rather young technological field in comparison. Here, the shares of SMEs have risen over the years from 18% in 1985-1989 to 35% in 2005-2008, where as the share of patent applications by MNEs has decreased from about 63% in 1985-1989 to 42% in the period 2005-2008. Universities (19% in 2005-2008) and public research institutes (9% in 2005-2008) both have a rather high share of patent applications within the field. Although the number is decreasing in the case of public research institutes, it has grown steadily over the last 25 years for universities.

Figure 6: Patent applications by applicant type in the respective field as a share of total patent applications by the respective applicant type, 1995-2008, patent applications from US and German applicants only

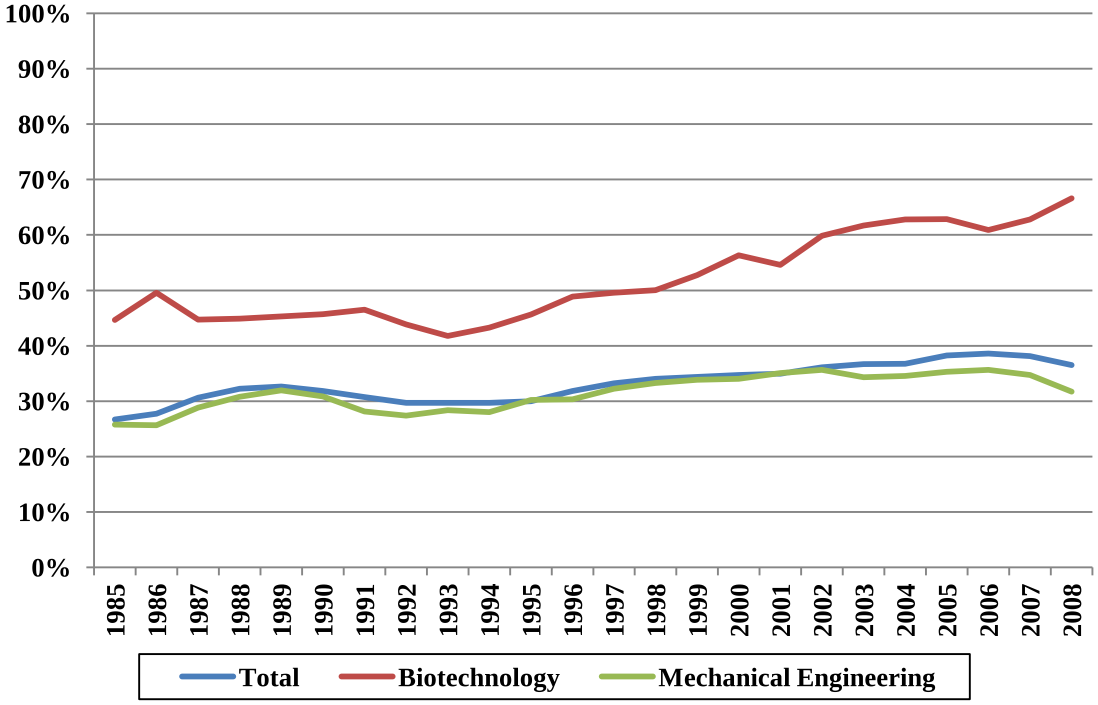


Source: EPO – PATSTAT, own calculations.

In Figure 6, we take a look at the patent applications differentiated by applicant type from another point of view. Namely, applicant-type-specific filings in green biotechnology and mechanical engineering as a share of all patent filings of the respective applicant type by US and German applicants covering the German market are shown. The most striking effect can be observed for universities and public research institutes in green biotechnology. In the period 1985-1989, 39% of all university patents were filed in the green biotechnology field. This share peaked at nearly 45% in the years 1990-1994 and went back to 24% in the period 2005-2008. Yet, still a large amount of university filings stem from green biotechnology. This trend can mostly be attributed to filings from US universities. The University of California alone has filed 1,104 patents within green biotechnology as defined by our IPC classes between 1985 and 2008. The Top10 patenting US universities, including the University of Texas, the University of Washington, the Harvard College, the MIT etc., make up more than one third of all green biotechnology filings from German and US applicants taken together, which alone equals about 12% of university patent filings across all technology fields in the whole time period. A similar effect can also be observed for public research institutes, but at a slightly lower level. When looking at these trends from the perspective of single IPC classes, it can be found that class C12N "MICRO-ORGANISMS OR ENZYMES […]" is responsible for the highest share of university patent filings, followed by class C07K "PEPTIDES" and C12Q "MEASURING OR TESTING PROCESSES INVOLVING ENZYMES OR MICRO-ORGANISMS […]". This, however, is not university-specific, as these IPC classes also have the highest shares in filings from SMEs, MNEs and public research institutes. In the case of SMEs and MNEs, the share of green biotechnology patents is rather small and below 5%, although the share is increasing over the years at least in the case of SMEs. These effects imply that universities as well as public research institutes have been relatively focused on green biotechnology within their portfolio. This trend, however, is decreasing until 2008.

In the mechanical engineering field on the other hand, the shares of universities and public research institutes are comparably lower. Less than 5% of patents filed by universities are coming from mechanical engineering, although this share is slightly increasing over the years. Public research institutes reach a share of 6% to 9% over the years, yet the trend is slightly decreasing since the period 1990-1994. A decreasing trend can also be observed for SMEs, although at a much higher level. The share of mechanical engineering patent filings from SMEs in all EPO and GPO patent filings from SMEs fell from 20% in 1985-1989 to 12% in the more recent years. For MNEs on the other side, the trend is increasing. 15% to 17% of all applications by MNEs originate from mechanical engineering.

Figure 7: International orientation (EPO applications of German applicants in relation to all filings covering the German market) of German patent filings in green biotechnology and mechanical engineering, 1985-2008



Source: EPO – PATSTAT, own calculations.
Note: The international orientation is calculated for German applicants only.

Finally, we take on the internationalization perspective to compare the two technology fields. Figure 7 shows EPO applications of German applicants in relation to all filings covering the German market in green biotechnology and mechanical engineering from 1985 to 2008. On average, the relation is around 32% over the years, rising from 27% in the year 1985, when the EPO was not yet frequented that often after its establishment in 1978, to 36% in 2008. This means that today more than one third of the patent applications by German applicants are filed also at the EPO and not solely at the GPO. A very similar trend can be observed for the mechanical engineering field, although at a slightly lower level than average at least in the recent years. For green biotechnology, however, the trend is different. In 2008, 67% of patents were filed at the EPO and not solely at the GPO. Although this number peaks in 2008, this does not seem to be a recent trend. Already in 1989, the share of EPO applications of German applicants in relation to all filings covering the German market was 45%. This means that, already starting from a very high degree of internationalization as measured by this patent indicator, green biotechnology became more and more internationalized with a rather massive increase from 1993 onwards.

3.1.2 Correlation Analysis

After having presented the patenting trends in mechanical engineering and green biotechnology, we now dig deeper into the data by comparing the two fields with regard to several patent-related dimensions, e.g. citation and legal status related variables. We thus first of all perform a correlation analysis that shows how strongly the field-specific patents, i.e. green biotechnology and mechanical engineering, differ on those dimensions as well as how strongly the patent dimensions are related to each other. The correlation analysis is shown in Table 2. Since the dataset covers not only mechanical engineering and green biotechnology patents but all patents filed at the EPO and GPO between 1985 and 2009, the results of the dummy variables always have to be compared against all patent applications or "the average patent application".

When taking a look at the citation-related indicators, one can see that green biotechnology patents have a significantly positive correlation with patent forward citations, implying that green biotechnology patents are cited more often by other patents than the average patent. The same is true for backward citations, although the effect is smaller in size. Also the number of NPL citations in green biotechnology is significantly higher than average, and the effect is strongly pronounced, which means that green biotechnology has a relatively close link to science. This also confirms the results we have found in Figure 5 and Figure 6, where the patenting trends were depicted. Regarding the technology cycle time, which is supposed to indicate the speed of innovation, we find a negative correlation. This means that the TCT is shorter in green biotechnology, implying that green biotechnology is a field that moves more quickly from old to new technologies than average.

Table 2: Pairwise correlations between the relevant variables

	Green bio-technology	**Mechanical engineering**	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**	**(j)**
Citation related indicators												
(a) Nr. of forward citations	0.104***	-0.036***										
(b) Nr. of backward citations	0.021***	-0.0007	0.200***									
(c) Nr. of NPL citations	0.247***	-0.052***	0.156***	0.400***								
(d) Technology cycle time (log)	-0.160***	0.145***	-0.140***	0.040***	-0.060***							
Legal status indicators$^{\alpha}$												
(e) Granted	-0.047***	0.046***	0.087***	0.087***	0.002*	0.037***						
(f) Withdrawn	0.055***	-0.020***	-0.030***	-0.138***	-0.032***	-0.007***	-0.524***					
(g) Refused	-0.011***	-0.003***	-0.013***	-0.051***	-0.017***	0.006***	-0.164***	-0.152***				
(h) Opposed	-0.006***	0.028***	0.070***	0.047***	0.015***	-0.002**	0.194***	-0.106***	0.015***			
(i) Fee payment (after 5 years) $^{\alpha}$	-0.059***	0.072***	0.093***	0.028***	-0.019***	0.031***	0.803***	-0.443***	-0.117***	0.186***		
Additional patent indicators												
(j) Nr. of IPC classes	0.286***	0.073***	0.158***	0.074***	0.125***	-0.085***	0.041***	0.037***	-0.015***	0.025***	0.071***	
(k) Family size	0.131***	-0.069**	0.170***	0.163***	0.125***	-0.075***	0.140***	-0.120***	-0.082***	0.055***	0.208***	0.235***

Source: EPO – PATSTAT, own calculations.

Note: Significance level ***<0.01, **<0.05, *<0.1. $^{\alpha}$ Data available for EPO filings only.

It is interesting to see that the opposite is true for mechanical engineering. Within this field, patents are cited less often than the general trend and have a smaller number of NPL citations, although both correlation coefficients are rather small in size, meaning that the distance to the average is not overly large. In the case of the TCT, we find a positive correlation, meaning that the TCT in mechanical engineering is longer than average, i.e. patents cited by mechanical engineering are older than the general patent on average.

When looking at the legal status variables, several other interesting patterns can be revealed. Green biotechnology patents are significantly less often granted than the average patent and are withdrawn more often. Mechanical engineering patents, on the other hand, are granted more often than the average patent and are withdrawn as well as refused less often. These patterns show that mechanical engineering patents more often meet the criteria of novelty, inventive step and industrial applicability than patents from green biotechnology.

Finally, the last two indicators analyzed here show that both, green biotechnology and mechanical engineering patents have a larger average number of IPC classes than other patents in general. The coefficient for green biotechnology, however, is larger in size than the coefficient for mechanical engineering. This means that green biotechnology patents on average are broader in a technological sense than mechanical engineering patents. In addition, the average family size for green biotechnology patents is larger than the average family size for patents from mechanical engineering, which implies that in general, a larger number of markets is covered by green biotechnology than by mechanical engineering patents.

Before interpreting these effects more deeply, we now turn to the multivariate analyses, which are able to entangle the effects of several of the patent characteristics and show which of these correlations persist when controlling for additional factors, e.g. the country of the applicant or the period of time in which the patent has been filed.

3.2 Multivariate results

Taking our analyses from section 3.1 one step ahead, this section presents the results of our multivariate analyses. As being stated in section 2.6, we calculated all models separately for EPO applications and patents filed directly at the GPO in order to separate the effects on patent filings that target an international market (EPO) and those filings that purely target the German national market (GPO direct).

The table/figure combination (Table 3) thus first of all summarizes the multivariate results for EPO patent filings and is a bit unusual to read. The table in the upper part shows the effects of the dichotomous technology field variables (separately for mechanical engineering and green biotechnology) on the different outcome variables, like granted patents, family size or the number of forward and backward citations.

The coefficients all are calculated in single regression models with the technology field variables as explanatory variables as well as the control variables. Therefore, on the left-hand side of the table, the response variables can be found. The presented coefficient is the coefficient of the technology field dummy variable on the respective outcome variable. Since the dummy variables are coded 1 if a patent belongs to the respective technology field under analysis and 0 otherwise, positive values of the coefficients mean that the probability to be in the respective outcome category is higher for firms from the respective field than for all patent applications on average, whereas negative values mean that the probability is lower than average.

The effects of the control variables, e.g. the type or the country of the applicant, as well as the time period dummies which are also a part of each of the regressions are not shown explicitly because they do not form the core of this analysis. Yet, the full results of all calculated regression models can be consulted in the annex (Table 5 and Table 6).

The citation-related indicators in the multivariate models closely resemble the results that have already been found in the correlation analysis, which was calculated on the basis of EPO as well as GPO patents, except for the number of backward citations. Controlling for other factors, the coefficient for backward citations is significantly negative in green biotechnology and significantly positive in mechanical engineering. This means that green biotechnology patents at the EPO can be assumed to be less broad in scope. However, the negative effect might also suggest that EPO patents in green biotechnology are more original in nature than the average patent, i.e. building on a smaller already existing knowledge stock. Yet, this could also be associated with the fact that compared to mechanical engineering, green biotechnology is a rather young technological field and the existing knowledge stock within the field is smaller per se. In the case of forward citations, NPL citations and technology cycle time, the results from the correlation analysis can be confirmed. Green biotechnology patents at the EPO are cited more often from subsequent patents than the average patent, whereas EPO patents from mechanical engineering are cited below average. This result first of all implies that EPO patents in green biotechnology are more often used in order to generate new technological trajectories (within green biotechnology or other sectors) and probably have a larger spill-over impact than patents from the mechanical engineering sector. As for the NPL citations, we can observe that green biotechnology patents at the EPO have more NPL citations than average and mechanical engineering patents less often cite scientific literature. This points to a stronger science link or closeness to science in green biotechnology. This effect is not overly surprising when looking at the technological life cycle of the two technology fields. Mechanical engineering is a rather mature field, where the technology has already diffused to the market and thus is more applied. Yet, the opposite is true for green biotechnology. This field is comparably young and still closer to basic science. Regarding the TCT, it can be shown that life cycles are shorter on average in green biotechnology, meaning that green biotechnology is a field that moves more quickly from old to new technologies than average, whereas the technological life cycles are longer than average in mechanical engineering.

In sum, the results from the citations-based indicators at the EPO point into the direction that green biotechnology is more heavily generating an explicit knowledge base upon which subsequent inventions can build upon, whereas it seems that explicit knowledge generation plays a smaller role in mechanical engineering, where knowledge is more often circulated implicitly.

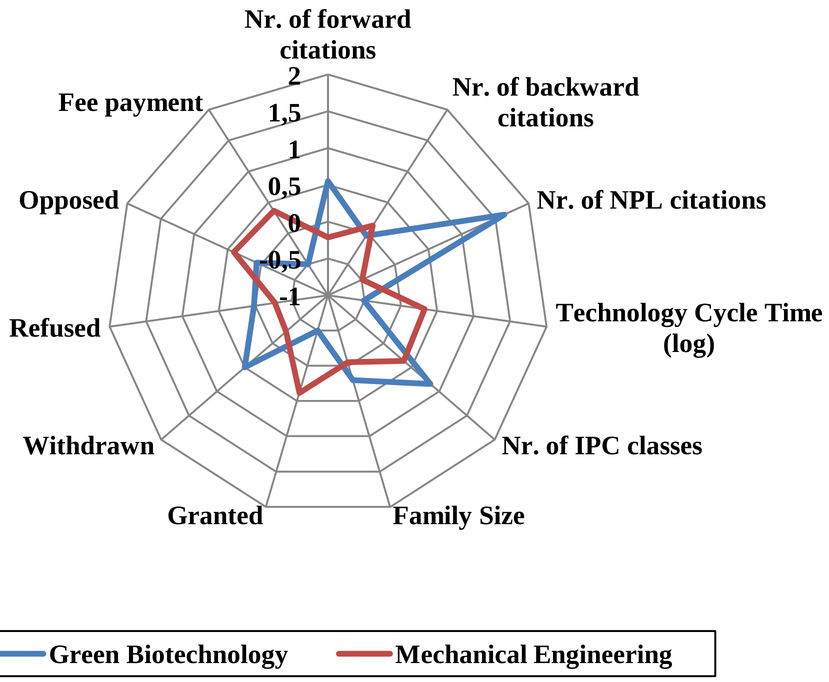
Now taking a look at the legal status indicators, it can be shown that patent applications from the field of mechanical engineering are granted more often by the EPO than average. The opposite is true for patent applications from green biotechnology. This first of all implies that patent filings from mechanical engineering more often meet the patenting criteria of novelty, inventive step and industrial applicability. However, there are several explanations for the discrepancy between the grant rates in the two technology fields. The easiest and most straightforward explanation would be that green biotechnology patents simply are of lesser technological quality than patents from mechanical engineering and thus are granted less often. The second and probably more likely explanation could be that patents in green biotechnology are used more often strategically in technology competition than patents from mechanical engineering. There are several reasons that support this explanation. The first one are the higher withdrawal rates in green biotechnology than in mechanical engineering, which points to the fact that these green biotechnology patents have had a strategic value to block competitors during their lifetime (Blind et al. 2006). In addition, the refusal rates in green biotechnology are not significantly lower than average, although a withdrawal can also mean an anticipated refusal (Harhoff/Wagner 2009). Furthermore, the technology life cycles in green biotechnology are shorter than average as shown by the coefficient of the TCT. This means that green biotechnology is a field that moves more quickly from older to newer technologies. Keeping in mind that it takes five to seven years on average until a patent is granted by the EPO (Frietsch et al. 2010), it might often be the case that patents in green biotechnology do not need maintained up to grant since the technology has already been replaced by a newer or improved one. A patent application thus already has a high option value (Gambardella et al. 2008; Harhoff/Wagner 2009) within this field. It blocks the relevant competitors within the same technology as long as it is alive. If the technology is replaced quickly, it can be withdrawn before grant, so no more fees have to be paid to the patent office. If a technology protected by the patent prevails, the patent application still might be kept within the system and eventually brought to grant. This pattern is also backed by the fee payment indicator, which is negative for green biotechnology patents and positive for mechanical engineering, implying that mechanical engineering patents are generally maintained for a longer period of time than green biotechnology patents.

Finally, taking a closer look at the opposition rates, it can be revealed that patents from both technology fields are opposed more often than the average patent, although the coefficient is higher in the case of mechanical engineering. This means that mechanical engineering patents are more often target of disputes than patents from biotechnology. It might be that the market for patented inventions is larger in mechanical engineering. However, since only granted patents can be opposed, it might also have to do with the lower grant rates in biotechnology as well as the shorter technology life cycles.

Last but not least, two indicators have not yet been discussed. The first one is the average number of IPC classes, which is higher than average in both technology fields. Yet, the coefficient is higher in green biotechnology than mechanical engineering implying that green biotechnology patents are technologically broader – i.e. span across a wider range of different technologies – than mechanical engineering patents. Also the family size of EPO patents is larger on average in green biotechnology than in mechanical engineering, where the average family size is even smaller than for the general patent. This means that a larger number of markets is sought to be secured by patents in green biotechnology, whereas patents from mechanical engineering on average target a smaller number of different markets.

Table 3: Main regression results for the EPO – Graphical and tabular summary

	Green bio-technology	Mechanical engineering	Obs.	R²	Regression type
Citation-related indicators					
Nr. of forward citations	0.552***	-0.212***	883209	0.025	Negative Binomial
Nr. of backward citations	-0.039***	0.125***	883209	0.008	Negative Binomial
Nr. of NPL citations	1.634***	-0.490***	883209	0.064	Negative Binomial
Technology cycle time (log)	-0.509***	0.327***	822084	0.0681	OLS
Legal status indicators					
Granted	-0.497***	0.387***	814248	0.155	Logit
Withdrawn	0.499***	-0.245***	814248	0.051	Logit
Refused	0.017	-0.269***	814248	0.041	Logit
Opposed	0.066**	0.409***	814248	0.059	Logit
Fee payment (after 5 years)	-0.502***	0.361***	803766	0.232	Logit
Additional patent indicators					
Nr. of IPC classes	0.843***	0.366***	882869	0.054	Zero Trunc. Neg. Bin.
Family size	0.203***	-0.050***	883209	0.008	Zero Trunc. Neg. Bin.



Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

Note: The differences in the coefficients cannot be compared across indicators since the different indicators are measured on different scale levels. In the logistic regression models, the Pseudo R² is used instead of R² McFadden. In the OLS model R² is employed. The full results of the respective models can be consulted in the annex.

All in all, the effects point towards the interpretation that green biotechnology patents are used more often strategically in technology competition in order to block competitors and patents are oftentimes used as "options", at least at the international (EPO) level. The observed patterns in mechanical engineering point to the fact that the traditional motive of protecting a technology from imitation by patenting stands in the foreground within this technology field. This could be explained by a higher risk of default in green biotechnology with which patent applicants try to cope by covering a large number of markets to hedge against market-related risks and spanning a wider range of technologies to hedge against technology-related risks.

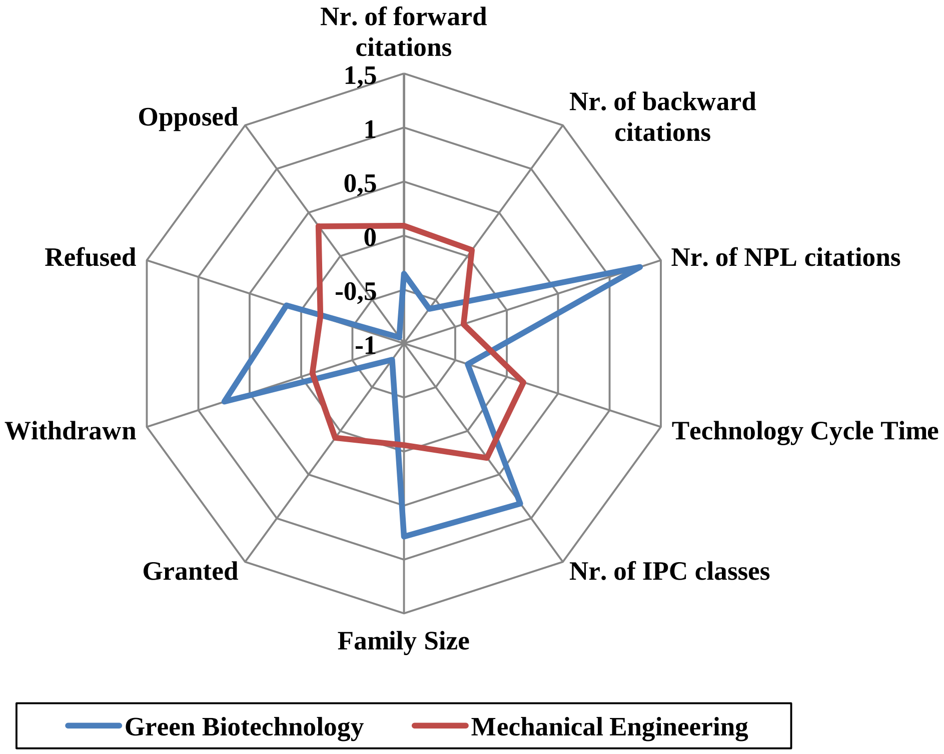
The table/figure combination in Table 4 now summarizes the multivariate results for the GPO patent filings, which enables us to separate the effects on patent filings that purely target the German national market compared to EPO patents analyzed above. The table needs to be read in a similar fashion as the table for EPO filings. The models all are calculated with the same dependent and independent variables and therefore can be interpreted in the same way as in the EPO model. The only difference is that the model for payment of maintenance fees cannot be calculated for GPO filings since there are no data available for this patent office.

It can be shown that most of the coefficients of the variables resemble the trends that have already been found for EPO patent filings, implying that there are only minor differences in national and international (EPO) patents in green biotechnology and mechanical engineering. There are only two indicators that stand out of this general trend. Namely, these are patent oppositions, and even more striking, patent forward citations. It can be shown that at the GPO, an opposition to a patent from biotechnology is a rather rare event. Green biotechnology patents are by far less often the target of an opposition than the average GPO patent. As for mechanical engineering, however, opposition is a more frequent event than average, which has also been found for EPO patents from that sector.

When looking at the forward citations indicator, it can be found that the coefficients switch signs compared to the EPO filings. This means that at the national level, mechanical engineering patents are cited more frequently than average, whereas green biotechnology patents are cited less often.

Table 4: Main regression results for the GPO – Graphical and tabular summary

	Green biotechnology	Mechanical engineering	Obs.	R²	Regression type
Citation-related indicators					
Nr. of forward citations	-0.354***	0.091***	550802	0.016	Negative Binomial
Nr. of backward citations	-0.603***	0.070***	550802	0.007	Negative Binomial
Nr. of NPL citations	1.297***	-0.419***	550802	0.021	Negative Binomial
Technology cycle time (log)	-0.380***	0.163***	388039	0.024	OLS
Legal status indicators					
Granted	-0.813***	0.080***	541754	0.040	Logit
Withdrawn	0.745***	-0.110***	541754	0.111	Logit
Refused	0.143***	-0.187***	541754	0.013	Logit
Opposed	-0.928***	0.343***	541754	0.039	Logit
Additional patent indicators					
Nr. of IPC classes	0.833***	0.308***	605968	0.014	Zero Trunc. Neg. Bin.
Family size	0.789***	-0.059***	606117	0.007	Zero Trunc. Neg. Bin.



Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

Note: The differences in the coefficients cannot be compared across indicators since the different indicators are measured on different scale levels. In the logistic regression models, the Pseudo R² is used instead of R² McFadden. In the OLS model R² is employed. The full results of the respective models can be consulted in the annex.

This implies that GPO patents in mechanical engineering are more often used in order to generate new technological trajectories and the spill-over effect within this sector is higher at the national level than at the EPO. In sum, this means that whereas green biotechnology is more heavily generating an explicit knowledge base upon which subsequent inventions can build upon at the international scale, this is not true for the national scale. At least in Germany, mechanical engineering is opening technological trajectories to a higher extent than green biotechnology.

4 Conclusion

The aim of this study was to analyze patent application structures and their evolution over time within the field of mechanical engineering and to compare these structures with a younger and growing technology field, namely green biotechnology. The background of the analyses is to try to find deeper insights about organizational knowledge generation and diffusion processes within the two technology fields.

Patents are a form of codified or explicit knowledge and reflect the knowledge capabilities or the knowledge stocks of the patenting entities (Frietsch/Schmoch 2006). A quantitative assessment of patenting structures and various additional dimensions of patenting, e.g. patent citations or legal status measures, can thus be considered a first step towards finding out more about knowledge generation within the mechanical engineering and green biotechnology fields.

In order to reach this aim, in a first step, a dataset based on the PATSTAT database was constructed, which allows us to analyze patenting structures via descriptive as well as via multivariate statistics, which is a necessary step towards learning more about the interrelation between the different patent characteristics within the two technology fields.

The descriptive analyses show that mechanical engineering has a relatively higher patent activity over the years than green biotechnology and green biotechnology patenting has rather decreased than risen in the recent years. However, one has to keep in mind the technological life cycle of the two technologies. Mechanical engineering can be said to have entered a phase known as diffusion phase (Dreher et al. 2005; Meyer-Krahmer/Dreher 2004) – which is characterized by a strong rise in patent applications through applied research in industry – a long time ago, whereas green biotechnology can still be considered to be in the disillusionment or re-orientation stage, in which scientific, technological and economic solutions from the early stages prove not to be sufficiently stable. Especially applied research and development plays a central role here and more and more companies offer technological solutions within or around this technology. Within this stage, patenting a large amount of new inventions by large firms still is in its infancy, yet the number of patents might grow significantly within the coming years. This can be backed by the fact that universities, public research institutes and also SMEs still make up a large share of green biotechnology patents, while patenting in mechanical engineering is mostly driven by large multinational companies.

Yet, it can also be stated that especially in Germany, green biotechnology is a rather small field in terms of patent applications. US applicants file a much larger number of green biotechnology patents. This, however, is not overly surprising since Germany traditionally has a focus on high-level technologies, with the mechanical engineering sector being the most prominent within its economy. Yet, although the share of green biotechnology patents from German applicants is rather small, the green biotechnology patents filed by German applicants are very internationally oriented, i.e. more often filed at the EPO than at the German Patent Office. This means that German applicants rather target foreign markets by filing green biotechnology patents than domestic markets, which is not true for mechanical engineering. Here, the domestic market is by far more important for the firms.

When differentiating the patent characteristics and its interrelations across the two fields via correlation analyses as well as multivariate regression models, several other interesting trends can be revealed.

The trends of the citation variables are very different between the two fields. Mechanical engineering patents are cited less often than other patents at the EPO, but are cited more heavily at the German Patent and Trademark Office. However, at both offices, they refer more often to previous patent literature, whereas the opposite is true for green biotechnology. In addition, green biotechnology seems to be linked closer to science than mechanical engineering, which is shown by the effects of the number of NPL citations. Furthermore, technology cycles are shorter in green biotechnology than in mechanical engineering. These results point into the direction that green biotechnology is more heavily generating an explicit knowledge base upon which subsequent inventions can build upon. Explicit knowledge generation seems to play a smaller role in mechanical engineering, where knowledge is more often circulated implicitly.

With regard to the legal status as well as the breadth of market coverage and breadth of technology classes, mechanical engineering and green biotechnology also are quite different. The revealed patterns show that green biotechnology patents seem to be used more often strategically in technology competition, e.g. to block competitors, and patents are oftentimes exercised as "options", whereas the protection of a technology against imitation by patenting seems to be more important in mechanical engineering. It seems that the risk of default is rather high in the younger green biotechnology field and the firms within the field try to hedge against these risks by covering a large number of markets and spanning patents across a wider range of technologies.

This has some important implications regarding the generation and diffusion of knowledge within the two fields. The citation trends show that spill-over effects as measured via patent forward citations are higher in green biotechnology, which however also could have to do with the development phase of the technology. In mechanical engineering, information or knowledge covered in patent applications does not spill-over to the same extent. Although it remains an assumption, since there are no data to control for the fact, mechanical engineering seems to be more reliant on knowledge generated in other sectors, as shown by the backward citation patterns, whereas green biotechnology generates knowledge that can subsequently be used in other technological areas. This could also be associated with the different patenting motives within the two fields. Strategic patenting motives seem to play a larger role in green biotechnology, whereas the traditional motive of protection from imitation seems to be a key motivation in mechanical engineering.

5 Annex

Table 5: Results of the Multivariate Regression Models I, EPO patent filings

	Negative binomial regression									OLS regression			Zero truncated negative binomial regression					
	Nr. of forward citations			Nr. of backward citations			Nr. of NPL citations			Technology Cycle Time (log)			Nr. of IPC classes			Family Size		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Biotechnology	0.552	***	0.009	-0.039	***	0.009	1.634	***	0.012	-0.509	***	0.004	0.843	***	0.003	0.203	***	0.003
Mechanical engineering	-0.212	***	0.007	0.125	***	0.005	-0.490	***	0.010	0.327	***	0.003	0.366	***	0.003	-0.050	***	0.002
SME	-0.200	***	0.006	0.053	***	0.003	0.125	***	0.010	0.136	***	0.002	-0.064	***	0.003	-0.062	***	0.002
University	-0.069	***	0.018	-0.159	***	0.010	0.764	***	0.017	-0.061	***	0.007	0.101	***	0.006	-0.091	***	0.005
Public research institute	0.137	***	0.014	-0.086	***	0.011	0.935	***	0.019	-0.074	***	0.006	0.102	***	0.005	-0.074	***	0.004
DE applicant	-0.291	***	0.005	0.073	***	0.003	-0.358	***	0.007	0.191	***	0.002	-0.185	***	0.002	-0.182	***	0.002
Cohort 2 (1990-1994)	0.096	***	0.010	0.173	***	0.006	0.309	***	0.013	-0.043	***	0.004	0.045	***	0.004	0.067	***	0.003
Cohort 3 (1995-1999)	0.335	***	0.009	0.439	***	0.004	0.501	***	0.012	-0.057	***	0.004	0.014	***	0.004	0.089	***	0.003
Cohort 4 (2000-2004)	-0.082	***	0.008	0.504	***	0.004	0.599	***	0.009	-0.074	***	0.003	-0.071	***	0.004	0.064	***	0.003
Cohort 5 (2005-2009)	-1.175	***	0.009	0.146	***	0.004	0.226	***	0.009	-0.016	***	0.003	-0.629	***	0.004	-0.070	***	0.003
Constant	1.006	***	0.008	1.690	***	0.004	0.464	***	0.008	1.695	***	0.003	0.453	***	0.004	1.735	***	0.002
Time-Dummies	YES			YES			YES			YES			YES			YES		
Observations	883209			883209			883209			822084			882869			883209		
R² McFadden/ Pseudo R²	0.025			0.008			0.064			0.068			0.054			0.008		
Wald chi²/F	55163.56			23844.33			51082.19			6008.34			161731.3			32273.13		
Prob > chi²/ Prob > F	0.000			0.000			0.000			0.000			0.000			0.000		

Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

Note: In the OLS regression and F-test is used instead of a Wald Chi² test. In the logistic regression models the Pseudo R² is used instead of R² McFadden.

Table 6: Results of the Multivariate Regression Models II, EPO patent filings

	Logistic regression														
	Granted			**Withdrawn**			**Refused**			**Opposed**			**Fee payment**		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Green biotechnology	-0.497	***	0.011	0.499	***	0.010	0.017		0.028	0.066	**	0.031	-0.502	***	0.011
Mechanical engineering	0.387	***	0.008	-0.245	***	0.008	-0.269	***	0.024	0.409	***	0.018	0.361	***	0.008
SME	-0.208	***	0.006	0.150	***	0.006	-0.144	***	0.018	-0.049	***	0.017	-0.242	***	0.007
University	-0.410	***	0.017	0.130	***	0.016	0.023		0.044	-0.270	***	0.057	-0.444	***	0.018
Public research institute	-0.188	***	0.018	0.048	***	0.018	0.113	**	0.050	-0.538	***	0.064	-0.221	***	0.020
DE applicant	0.739	***	0.005	-0.347	***	0.006	-0.213	***	0.015	0.617	***	0.014	0.681	***	0.006
EPO filing			--			--			--			--			--
Cohort 2 (1990-1994)	0.013		0.010	-0.040	***	0.010	-0.066	***	0.022	-0.050	**	0.021	0.092	***	0.010
Cohort 3 (1995-1999)	-0.659	***	0.009	0.282	***	0.009	-0.479	***	0.021	-0.365	***	0.021	-0.324	***	0.009
Cohort 4 (2000-2004)	-1.268	***	0.009	0.015	*	0.009	-0.940	***	0.022	-0.940	***	0.022	-1.437	***	0.009
Cohort 5 (2005-2009)	-2.992	***	0.011	-1.314	***	0.011	-2.296	***	0.039	-2.746	***	0.046	-7.763	***	0.096
Constant	0.402	***	0.008	-0.794	***	0.008	-2.890	***	0.018	-3.330	***	0.019	0.141	***	0.008
Time-Dummies	YES			YES			YES			YES			YES		
Observations	814,248			814,248			814,248			814,248			803,766		
Pseudo R²	0.155			0.051			0.041			0.059			0.2324		
Wald chi²	125286.63			36607.11			5698.34			9533.67			78755.53		
Prob > chi²	0.000			0.000			0.000			0.000			0.000		

Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

Table 7: Results of the Multivariate Regression Models III, GPO patent filings

	Negative binomial regression									OLS regression			Zero truncated negative binomial regression					
	Nr. of forward citations			Nr. of backward citations			Nr. of NPL citations			Technology Cycle Time (log)			Nr. of IPC classes			Family Size		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Biotechnology	-0.354	***	0.026	-0.603	***	0.025	1.297	***	0.043	-0.380	***	0.014	0.833	***	0.008	0.789	***	0.013
Mechanical engineering	0.091	***	0.007	0.070	***	0.004	-0.419	***	0.014	0.163	***	0.003	0.308	***	0.004	-0.059	***	0.005
SME	-0.244	***	0.007	0.123	***	0.004	0.055	***	0.013	0.178	***	0.003	-0.148	***	0.004	-0.363	***	0.005
University	-0.012		0.017	0.167	***	0.010	1.179	***	0.019	-0.006		0.007	0.085	***	0.009	-0.276	***	0.012
Public research institute	-0.249	***	0.034	0.139	***	0.018	1.629	***	0.040	0.013		0.012	0.044	***	0.016	-0.599	***	0.024
DE applicant	0.618	***	0.013	0.456	***	0.009	0.615	***	0.026	0.140	***	0.006	-0.092	***	0.006	-0.408	***	0.006
Cohort 2 (1990-1994)	0.436	***	0.012	0.368	***	0.009	0.361	***	0.019	-0.008		0.007	0.093	***	0.007	-0.073	***	0.008
Cohort 3 (1995-1999)	0.640	***	0.011	0.401	***	0.008	0.159	***	0.018	-0.062	***	0.006	0.032	***	0.006	-0.039	***	0.008
Cohort 4 (2000-2004)	0.248	***	0.011	0.361	***	0.008	-0.394	***	0.019	-0.110	***	0.006	-0.012	**	0.006	-0.074	***	0.007
Cohort 5 (2005-2009)	-0.351	***	0.012	0.680	***	0.008	0.221	***	0.020	0.008		0.006	-0.199	***	0.006	-0.349	***	0.007
Constant	-0.786	***	0.016	0.114	***	0.011	-1.875	***	0.029	1.836	***	0.008	0.165	***	0.008	0.916	***	0.010
Time-Dummies	YES			YES			YES			YES			YES			YES		
Observations	550802			550802			550802			388039			605968			606117		
R² McFadden/ Pseudo R²	0.016			0.007			0.021			0.024			0.014			0.007		
Wald chi²/F	17614.20			15249.17			11397.96			950.96			22123.83			19127.82		
Prob > chi²/ Prob > F	0.000			0.000			0.000			0.000			0.000			0.000		

Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

Note: In the OLS regression and F-test is used instead of a Wald Chi² test. In the logistic regression models the Pseudo R² is used instead of R² McFadden.

Table 8: Results of the Multivariate Regression Models IV, GPO patent filings

	Logistic regression											
	Granted			Withdrawn			Refused			Opposed		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Biotechnology	-0.813	***	0.027	0.745	***	0.024	0.143	***	0.035	-0.928	***	0.121
Mechanical engineering	0.080	***	0.007	-0.110	***	0.008	-0.187	***	0.012	0.343	***	0.021
SME	0.379	***	0.007	-0.225	***	0.007	0.159	***	0.011	0.496	***	0.020
University	0.943	***	0.017	-0.939	***	0.021	0.213	***	0.027	-0.120	*	0.066
Public research institute	0.399	***	0.033	-0.324	***	0.036	0.417	***	0.047	-0.411	**	0.160
DE applicant	0.094	***	0.013	0.356	***	0.013	0.051	**	0.020	0.691	***	0.053
Cohort 2 (1990-1994)	1.084	***	0.013	-0.864	***	0.012	-0.177	***	0.020	0.454	***	0.034
Cohort 3 (1995-1999)	1.166	***	0.012	-1.152	***	0.011	0.103	***	0.017	0.216	***	0.033
Cohort 4 (2000-2004)	0.718	***	0.012	-1.460	***	0.011	0.036	**	0.017	-0.462	***	0.035
Cohort 5 (2005-2009)	0.135	***	0.013	-3.096	***	0.014	-0.780	***	0.020	-1.218	***	0.045
Constant	-1.635	***	0.017	0.635	***	0.016	-2.281	***	0.024	-4.551	***	0.061
Time-Dummies	YES			YES			YES			YES		
Observations	541754			541754			541754			541754		
R^2 McFadden/ Pseudo R^2	0.040			0.111			0.013			0.039		
Wald chi²/F	26165.77			59252.29			3939.29			3920.4		
Prob > chi²/ Prob > F	0.000			0.000			0.000			0.000		

Source: EPO - PATSTAT, own calculations.

Significance level: ***<0.01, **<0.05, *<0.1.

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